Automatic detection of damaged electrical insulators in power-lines using deep learning

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Abstract

Identification of damaged insulators is important to protect humans from highly dangerous high voltage electric current. Here we develop and test multiple approaches to automatic identification of damaged insulators. Tested approaches include multiple deep neural networks, as well as shallow learning methods. Best results of 86.4% are achieved when using the AdeNet architecture. While the method cannot fully replace human inspection, its high throughput can reduce the amount of labor required to monitor for damaged insulator, while providing early warning to replace damaged insulators.

1 Introduction

Power-line insulators undergo changes with time as a result of continuous exposure to hazardous weather conditions. In this work, we explore various classification techniques to classify automatically power-line electrical insulators as either damaged or undamaged.

For the purpose of identification of damaged insulators we developed a deep learning architecture, named AdeNet, that performs well without pre-training. Also, AdeNet eliminates the various data augmentation overheads discussed in [1]. As a result, our model requires less computation and storage, making it more suitable for the computing capabilities of mobile/embedded devices such as unmanned aerial vehicles (UAV). Analysis on the device can be used for decisions of whether the acquire additional data while the UAV is still on its mission.

AdeNet is compared with state-of-the-art DL architectures and shallow learning (SL) techniques. To provide model trust justification, we use heatmap visualization tool by Grad-CAM [2] to inspect model's attention while making predictions.

2 Methods

In deep learning, multiple layers of mini-algorithms, called “neurons", work together to draw complex conclusions. We experiment with a number of DL architectures from basic LeNet-5 to more complex ResNet, VGG19 and MobileNetV2. Our architecture, named AdeNet, is also designed for comparison purpose.

2.1 AdeNet

AdeNet is a deep learning architecture implemented with three layers of Convolutional Neural Networks (CNNs) each with batch normalization, maxpooling and relu with no dropout, then follows one fully connected layer before the softmax layer. The architecture contains the initial fully convolutional layer with 32 filters. We always use kernel size 3 x 3 as is standard for modern

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networks. The trained model size is 1.3MB and has 102, 082 trainable parameters and 448 non-trainable parameters.

2.2 Shallow learning

We also attempted to use shallow learning. That included the extraction of numerical image content descriptors using the UDAT algorithm [3], and then applying several classification algorithms, including Gradient Boosting, Multilayer Perceptron, and random forests.

3 Data

The dataset which is provided by our project sponsor, BlackAndVeatch, consists of 1696 power-line JPEG images of dimensions 5280x3956, and resolution 72x72. We randomly divide the entire dataset into 80% training and 20% test set. Each image is annotated with a bounding-box around the object of interests which are the insulators. The insulators are broadly categorized as damaged (positive class) and undamaged (negative class).

4 Results

The results of of applying the algorithms described in Section 2 to the data described in Section 3 are shown in Table 2. Table 1 shows the confusion matrix when using AdeNet, which was the method providing the highest classification accuracy.

Table 1: Confusion matrix for AdeNet after 20 epochs for test set

	Damaged	Undamaged
Damaged	1026	424
Undamaged	213	3962

Table 2: Classification accuracy, F1, precision, recall, and ROC area under the curve when using different methods.

Dataset	Classifiers	Acc	F1	Precision	Recall	ROC Area	#folds
val	RandomForest	85.7	0.850	0.857	0.857	0.915	10
val	MultiLayer Perceptron	81.8	0.816	0.815	0.818	0.855	10
val	GradientBoosting	87	-	-	-	-	
val	LeNet5	68	0.445	0.71	0.52	0.51	1
val	AdeNet + 10 epochs	86	82.7	87.4	81.1	-	5
test	AdeNet + 10 epochs	86.4	81	84.8	79.7	0.7972	5
test	AdeNet + 20 epochs	-	-	-	-	0.8274	5
val	EfficientNetB7	65	0.545	0.57	0.55	0.55	1
val	VGG19	67	0.4	0.335	0.5	0.5	1
val	ResNet	67	0.42	0.67	0.505	0.51	1
test	MobileNetV2 + 10 epochs	81.6	0.72	0.769	0.712	0.73	5
test	MobileNetV2 + 20 epochs	70.4	0.628	0.759	0.7	0.71	5

References

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